Hydrological responses of land use change from cotton (*Gossypium hirsutum L.*) to cellulosic bioenergy crops in the Southern High Plains of Texas, USA

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Abstract

The Southern High Plains (SHP) region of Texas in the United States, where cotton is grown in a vast acreage, has the potential to grow cellulosic bioenergy crops such as perennial grasses and biomass sorghum (*Sorghum bicolor*). Evaluation of hydrological responses and biofuel production potential of hypothetical land use change from cotton (*Gossypium hirsutum L.*) to cellulosic bioenergy crops enables better understanding of the associated key agroecosystem processes and provides for the feasibility assessment of the targeted land use change in the SHP. The Soil and Water Assessment Tool (SWAT) was used to assess the impacts of replacing cotton with perennial Alamo switchgrass (*Panicum virgatum L.*), *Miscanthus × giganteus* (*Miscanthus sinensis* Anderss. [Poaceae]), big bluestem (*Andropogon gerardii*) and annual biomass sorghum on water balances, water use efficiency and biofuel production potential in the Double Mountain Fork Brazos watershed. Under perennial grass scenarios, the average (1994–2009) annual surface runoff from the entire watershed decreased by 6–8% relative to the baseline cotton scenario. In contrast, surface runoff increased by about 5% under the biomass sorghum scenario. Perennial grass land use change scenarios suggested an increase in average annual percolation within a range of 3–22% and maintenance of a higher soil water content during August to April compared to the baseline cotton scenario. About 19.1, 11.1, 3.2 and 8.8 Mg ha^{-1} of biomass could potentially be produced if cotton area in the watershed would hypothetically be replaced by *Miscanthus*, switchgrass, big bluestem and biomass sorghum, respectively. Finally, *Miscanthus* and switchgrass were found to be ideal bioenergy crops for the dryland and irrigated systems, respectively, in the study watershed due to their higher water use efficiency, better water conservation effects, greater biomass and biofuel production potential, and minimum crop management requirements.

Keywords: big bluestem, biofuel, biomass, biomass sorghum, *Miscanthus*, semi-arid region, Soil and Water Assessment Tool, switchgrass, water balances

Introduction

The semi-arid Southern High Plains (SHP) of Texas in the United States is one of the most agriculturally intensive regions in the world. Irrigated agriculture in the SHP depends primarily on groundwater availability in the underlying vast Ogallala aquifer. About 97% of water withdrawn from the Ogallala aquifer is used for crop irrigation in the SHP (Maupin & Barber, 2005). However, groundwater levels in this region are experiencing a continuous decline due to much higher rates of groundwater extraction compared to recharge (Chaudhuri & Ale, 2014; Rajan *et al.*, 2015). Many producers in this region are facing water shortages due to lower groundwater availability and higher pumping costs (Nair *et al.*, 2013). To extend the life of the Ogallala aquifer and to insure that at least certain percentage (varies with the water district) of currently available groundwater will still be available in 2060, the primary regulatory agencies in the region imposed new rules to limit the allowable annual groundwater pumping for irrigation. For example, the High Plains Underground Water Conservation District (http://www.hpwd.org/) sets the pumping limit for 2015 at 46 cm (HPUWCD, 2015).

The major crop grown in the SHP region is cotton, and this region produced approximately 13% of U.S. cotton in 2013 (NASS, 2013). The new restrictions on

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groundwater pumping in the SHP are expected to result in a change in land use from high-water-demanding crops such as cotton and corn to relatively less water demanding crops in the near future (Rajan *et al.*, 2014). The agricultural land in the SHP region has the potential to grow cellulosic bioenergy crops such as perennial grasses and biomass sorghum (*Sorghum bicolor*) (USDA, 2010), which have higher water use efficiency compared to cotton, and can provide water quality and economic benefits (Rooney *et al.*, 2007; Sarkar *et al.*, 2011; Kiniry *et al.*, 2013; Sarkar & Miller, 2014). The United States Department of Agriculture (USDA) has also estimated that about 11.4% of existing croplands and pastures in the southeastern U.S. region, which includes the SHP, will be required for fuel use for meeting the 2022 national cellulosic biofuel target (USDA, 2010).

A potential land use change from croplands to cellulosic bioenergy crops in the SHP may significantly affect regional hydrologic cycle by altering proportions of surface runoff, water yield (the net amount of water that generates from a landscape and contributes to streamflow during a given time interval), evapotranspiration (ET), soil water content and percolation (the amount of water that percolates below the root zone during a given time). For example, Schilling *et al.* (2008) found that the land use from cropland to cellulosic bioenergy crop of switchgrass in the Raccoon River watershed in west-central Iowa would increase ET by about 9% and decrease water yield by about 28%. VanLoocke *et al.* (2010) also reported that the land use conversion from corn (*Zea mays L.*) to perennial biofuel grasses would increase ET within a range of 50–150 mm year^{-1} and decrease the drainage within a range of 50–250 mm year^{-1} in the Corn Belt of Midwestern United States. Majority of these biofuel-induced land use change studies focused on the humid regions of the United States such as the Upper Mississippi River Basin of the Corn Belt region (Srinivasan *et al.*, 2010; Demissie *et al.*, 2012; Zhuang *et al.*, 2013). Such detailed assessments of hydrological impacts of biofuel-induced land use change are lacking for the arid/semi-arid regions such as the SHP. In addition, no comprehensive assessment of hydrological responses and biofuel production potential of land use change from major row crops such as cotton to various cellulosic bioenergy crops are documented (Sarkar & Miller, 2014). Evaluating the hydrologic impacts of land use change from cotton to cellulosic bioenergy crops in the semi-arid SHP is therefore necessary to assess the feasibility of the proposed land use change.

The potential for the use of cellulosic crops such as Alamo switchgrass (*Panicum virgatum L.*), *Miscanthus × giganteus* (*Miscanthus sinensis* Anderss. [Poaceae]), big bluestem (*Andropogon gerardii*) and biomass

sorghum as bioenergy crops was studied by several researchers in different parts of the world through field experimentation and modeling (Wright, 2007; Heaton *et al.*, 2008; Jain *et al.*, 2010; Qin *et al.*, 2011, 2014; Zhuang *et al.*, 2013; Yimam *et al.*, 2014, 2015; Zatta *et al.*, 2014; Oikawa *et al.*, 2015; Zhang *et al.*, 2015a). Alamo switchgrass is a perennial C4 warm-season bunch grass native to North America, and it is found in low, moist areas and prairies of north-central Texas (Diggs *et al.*, 1999). *Miscanthus × giganteus* is a C4 cool-season grass (Heaton *et al.*, 2004, 2008) that is native to Southeast Asia (Ohwi, 1964) and Africa (Adati & Shiotani, 1962). Big bluestem is a C4 warm-season perennial native grass that comprises as much as 80% of the plant biomass in prairies in the Midwestern grasslands of North America (Gould & Shaw, 1983; Knapp *et al.*, 1998). Biomass sorghum is a photoperiod-sensitive C4 type lignocellulosic biomass crop that remains in a vegetative growth stage for most of the growing season in subtropical and temperate climates (Rooney *et al.*, 2007). In this study, *Miscanthus × giganteus*, Alamo switchgrass, big bluestem and biomass sorghum were selected to hypothetically replace the existing cotton land use (baseline). Alamo switchgrass has higher radiation-use efficiency and water use efficiency than Kanlow and other switchgrass varieties (Blackwell, Cave-in-Rock, and Shawnee) in the Southern Great Plains (Kiniry *et al.*, 2013), and hence, Alamo switchgrass was selected in this study.

Several hydrologic models are available for simulating the hydrological impacts of land use change, such as the Soil and Water Assessment Tool (SWAT; Arnold *et al.*, 1998), Agricultural Policy/Environmental Extender (APEX) model (Williams, 1995), European Hydrological System Model MIKE SHE (Refsgaard & Storm, 1995), DRAINMOD (Youssef *et al.*, 2005; Skaggs *et al.*, 2012) and the Agricultural Drainage and Pesticide Transport (ADAPT) model (Gowda *et al.*, 2012). Among these models, the SWAT model has been used widely across the world and it demonstrated potential to satisfactorily predict long-term impacts of land use change on hydrologic processes in complex watersheds (Ghaffari *et al.*, 2010; Srinivasan *et al.*, 2010; Wu & Liu, 2012; Zatta *et al.*, 2014), and hence, the same model was used in this study. The availability of good quality observed streamflow data is vital for developing a well-calibrated SWAT model for the study watershed. There are only a limited number of USGS gauges in the SHP region and they recorded very low streamflow in most parts of the year, which posed some challenges for the SWAT model calibration. Several recent studies used crop yield as an auxiliary data for model calibration, as crop yield is directly proportional to ET component of the water balance (Akhavan *et al.*, 2010; Srinivasan *et al.*, 2010; Zhang *et al.*, 2013, 2015b; Mittelstet *et al.*, 2015). This additional

step in model calibration gives more confidence on the partitioning of water between soil storage, ET and aquifer recharge (Faramarzi *et al.*, 2009, 2010; Akhavan *et al.*, 2010). Therefore, the SWAT model was calibrated against reported county-level cotton lint yield data in addition to streamflow.

The overall goal of this study was to evaluate the hydrological responses and biofuel production potential of hypothetical land use change from cotton to cellulosic bioenergy crops including two native perennial grasses, switchgrass and big bluestem; one non-native perennial grass, *Miscanthus*; and an annual, high potential biofuel crop of biomass sorghum in the Double Mountain Fork Brazos watershed in the SHP using the SWAT model. In the SWAT crop database, big bluestem and biomass sorghum are included as generic crops, and hence, we modeled these two crops as generic crops instead of specific varieties. Specific objectives of the study were to (1) assess the impacts of hypothetical land use change from cotton to bioenergy crops such as switchgrass, *Miscanthus*, big bluestem and biomass sorghum on water balances; (2) quantify the potential amount of biofuel production from these cellulosic bioenergy crops and identify appropriate bioenergy crops for the SHP region; and (3) compare and contrast the hydrologic impacts and biofuel production potential of the proposed hypothetical land use changes under irrigated and dryland agricultural systems.

Materials and methods

Watershed description

The Double Mountain Fork Brazos watershed (HUC # 12050004) in the SHP has a total delineated area of about 6000 km^2. Larger parts of the watershed are located in the counties of Hockley, Lynn, Garza, Scurry, Kent and Stonewall, and some smaller portions in Terry, Lubbock, Dawson, Borden, Fisher and Haskell Counties (Fig. 1). The long-term (1981–2010) average annual precipitation across the watershed varies between 457 and 559 mm, and the long-term average annual maximum and minimum temperatures are about 23°C to 25°C and 8°C to 10°C, respectively. The topography of the watershed is flat, and there is a long history of cotton and winter wheat (*Triticum aestivum*) cultivation in this watershed. The primary soil types in the watershed are Amarillo sandy loam (fine-loamy, mixed, superactive and thermic Aridic Paleustalfs), Acuff sandy clay loam (fine-loamy, mixed, superactive and thermic Aridic Paleustolls) and Olton clay loam (fine, mixed, superactive and thermic Aridic Paleustolls) (Soil Survey Staff, 2010).

Seven weather stations with daily precipitation and minimum and maximum temperature data exist inside or within a closer distance of the watershed. Although three USGS gauges are located in this watershed, the streamflow data from only two gauges (08079600, which is denoted as Gauge I and

08080500, which is at the watershed outlet and denoted as Gauge II) were used in this study (Fig. 1). Data from the remaining gauge were not used to calibrate the SWAT model as only limited streamflow data pertaining to 1949–1951 period was available for that gauge (08080000).

SWAT model description

The SWAT model is a continuous-time, semidistributed, process-based, river basin scale model (Arnold *et al.*, 2012). A large number of input parameters are needed for SWAT to evaluate the effects of land use change on hydrology and water quality. SWAT is operated on a daily time step and is widely proven as a feasible tool to predict the impact of land use and management on water, sediment and agricultural chemical yields in many watersheds (Gassman *et al.*, 2014). The primary model components in SWAT include the pesticide, hydrology and crop growth (Knisel, 1980; Leonard *et al.*, 1987; Williams *et al.*, 2008; Wang *et al.*, 2011). Major model inputs are related to hydrography, terrain, land use, soil, tile, weather and management practices (Srinivasan *et al.*, 2010).

In this study, ArcSWAT (Version 2012.10_2.16 released on 9/9/14) for ArcGIS 10.2.2 platform was used. The SWAT Calibration and Uncertainty Procedure (SWAT-CUP) (Abbaspour *et al.*, 2007), a program that has been frequently used for sensitivity analysis, calibration, validation and uncertainty analysis of SWAT models (Chandra *et al.*, 2014; Vaghefi *et al.*, 2014), was used in this study. Currently, SWAT-CUP 2012 can link Generalized Likelihood Uncertainty Estimation (GLUE; Beven & Binley, 1992), Parameter Solution (Van Griensven & Meixner, 2006), Sequential Uncertainty Fitting version-2 (SUFI-2; Abbaspour *et al.*, 2007) and Markov chain Monte Carlo procedures (Marshall *et al.*, 2004) to SWAT. In this study, SWAT-CUP 2012 SUFI-2 procedure was used to accomplish the model sensitivity analysis, calibration and validation, and estimation of various SWAT parameters related to streamflow.

SWAT model setup

Digital elevation model. The Digital elevation model (DEM) of the watershed, with a horizontal resolution of 30 × 30 m, was downloaded from the U.S. Geological Survey (http://viewer.nationalmap.gov/viewer/#) and input to the SWAT model. The DEM was used for estimation of watershed topography-related parameters for the study watershed.

Land use, soils and slope. The 2008 National Agricultural Statistics Service (NASS) Cropland Data layer (CDL) (http://nassgeodata.gmu.edu/CropScape/) was used as a land use input to the model to appropriately represent the land use condition of the simulated period from 1994 to 2009. The dominant agricultural land uses in the watershed in 2008 were cotton and winter wheat, which occupied about 30% and 2% of the watershed area (Fig. 2). About 41% and 21% of the watershed area were covered by range brush and range grass, respectively. The data of finer-scale soils from the Soil Survey Geographic Database (SSURGO) (Soil Survey Staff, 2014), which was compatible to ArcSWAT 2012, were used. The
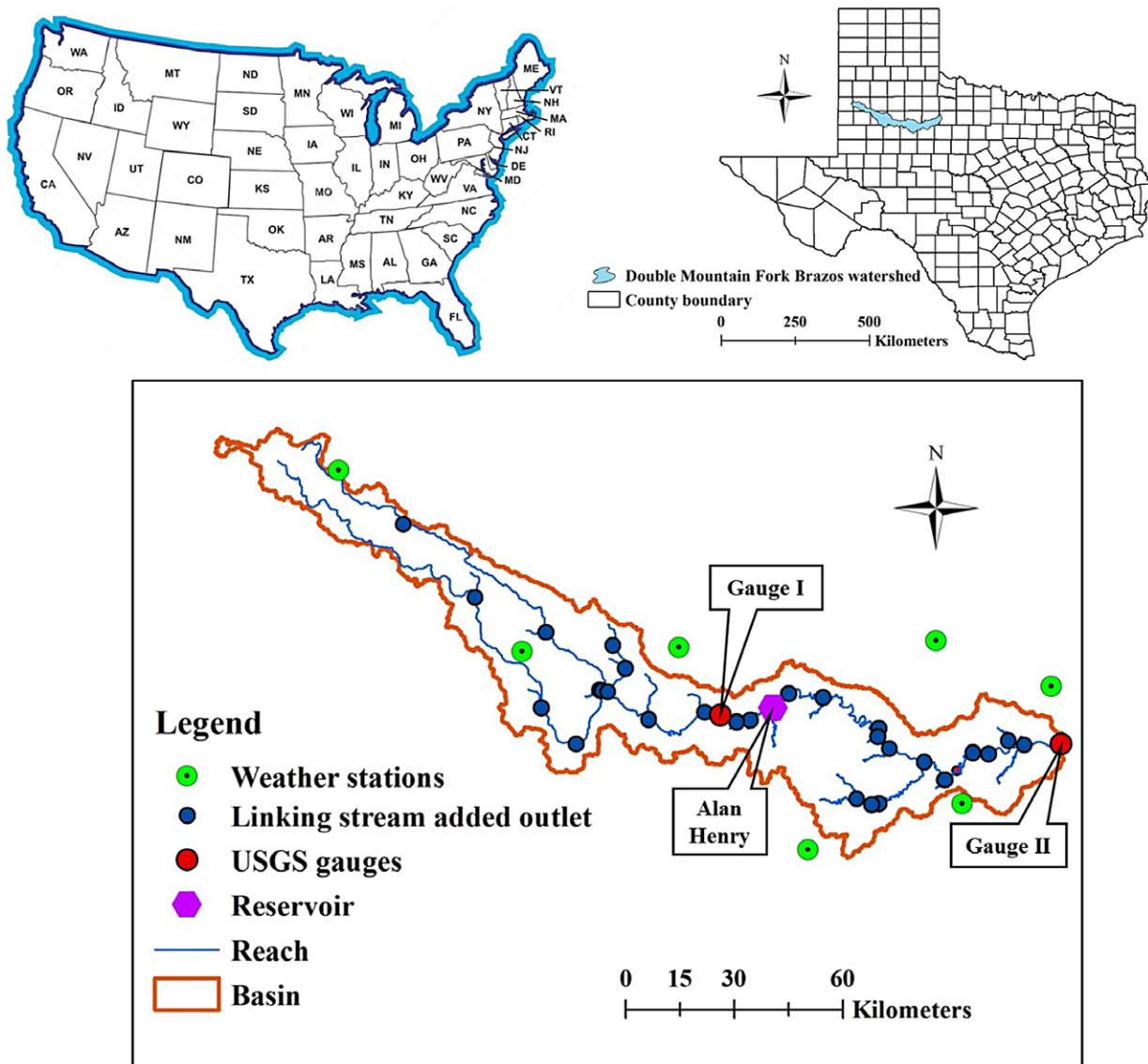
Fig. 1 Location of the study watershed.

watershed was classified into four groups according to soil slope: ≤ 1%, 1%–3%, 3%–5% and > 5%.

Hydrologic response units. The hydrologic response units (HRUs) are the basic building blocks of the SWAT model, from which all landscape processes are computed. The HRUs consist of homogeneous land use, soil characteristics and soil slope. For the HRU definition, thresholds of 5%, 5% and 10% were used for land use, soil type and slope, respectively. The number of sub-basins and HRUs identified for this watershed was 60 and 2160, respectively.

Weather. Daily weather data were obtained from the National Climatic Data Center (NCDC) for the period from 1992 to 2009 (NOAA-NCDC, 2014) and used in this study. Data from a total of seven weather stations, which were located either inside or within a closer distance of the study watershed, were used (Fig. 1). These weather stations were very well distributed spatially across the watershed. The missing precipitation, maximum temperature and minimum temperature data for a weather station were manually filled with the average value of weather parameter for two adjacent weather stations (Ale *et al.*, 2009).

Management practices of crops. Crop management related parameters for two dominant row crops, cotton and winter wheat, were set at appropriate values observed in the study area based on published reports, local expertise and web resources. The management parameters for other land uses were mostly kept at their default values. In this study, management practices in the SWAT model were scheduled by date. Generic spring plowing and generic fall plowing, which were
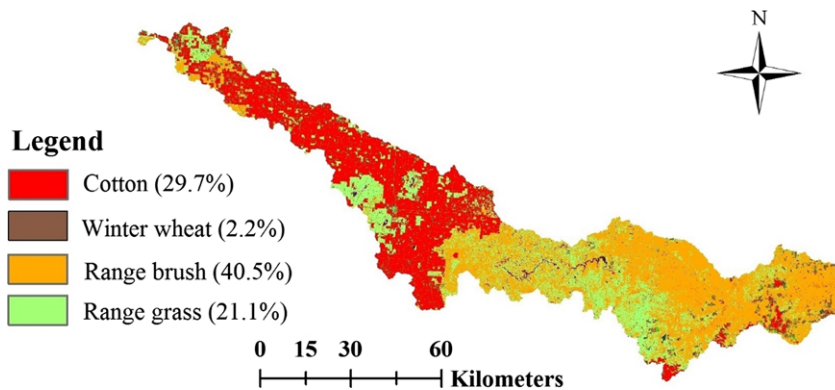
Fig. 2 Major land uses in the study watershed.

widely adopted tillage practices in this watershed, were used in cotton and winter wheat growing areas, respectively (Table 1). About 300 and 150 kg ha^{-1} of urea were applied to the irrigated and dryland cotton HRUs, respectively. About 108 kg ha^{-1} of urea was used for the winter wheat, which was grown under dryland systems. According to the published county-wise cotton acreage estimates over the period from 1994 to 2009 (NASS, 2014), about 39% of the cotton acreage in the watershed was irrigated. In this study, auto-irrigation was therefore simulated in an appropriate number of cotton HRUs so that about 39% of cotton acres in the watershed were irrigated. The auto-irrigation operation applied water whenever 10% reduction in plant growth occurred due to water stress (Table 1). Shallow aquifer was assigned as the source of irrigation water for the irrigated sub-basins.

Reservoir. Alan Henry, a big reservoir, exists in the study watershed, and operation parameters for this reservoir were obtained from the Texas Water Development Board's report on Volumetric Survey of Alan Henry reservoir (Texas Water Development Board, 2005). The reservoir surface area when the reservoir was filled to the emergency and principal spillways was about 1215 and 1109 ha, respectively. Volume of water needed to fill the reservoir to the emergency and principal spillways was estimated as 12688.3 × 10^4 and 11694.4 × 10^4 m^3, respectively. Average value of initial reservoir volume was taken as 4882.1 × 10^4 m^3, which was calculated based on the reservoir storage level records of the USGS gauge 08079700. Although the reservoir was operated from 1994, continuous daily reservoir release data were available only from 1997 to 2003. A relationship between the reservoir releases and annual rainfall was established based on the observed data for the 1997–2003 period, and the developed relationship was used to fill the missing reservoir release data for the 1994–1996 and 2004–2009 periods. Finally, the 'Measured Daily Outflow' method available in the SWAT model was used to estimate the reservoir discharge based on the reservoir storage levels recorded by the USGS gauge.

Observed streamflow and cotton lint yield. Observed daily streamflow data recorded at Gauges I and II over the time period from 1994 to 2009 were obtained from the USGS National

Water Information System (http://waterdata.usgs.gov/nwis/sw). The observed cotton lint yield data (under both dryland and irrigated systems) for the period from 1994 to 2009 for the Lynn County in the study watershed, in which the highest cotton acreage was reported, were obtained from the National Agricultural Statistics Service (NASS) reports (http://quick-stats.nass.usda.gov/). However, the SWAT model simulates whole cotton yield (seed cotton yield), which comprises of both cotton seed and lint. To compare with the observed cotton lint yield data obtained from the NASS, the simulated seed cotton yield was converted to lint yield using the following equation:

$$Y_{lint} = 0.39 \times Y_{whole} \qquad (1)$$

where Y_{lint} is the simulated lint yield (Mg ha^{-1}) and Y_{whole} is the simulated seed cotton yield (Mg ha^{-1}). The conversion factor of 0.39 was obtained from the relationship: about 340 kg cotton seed is equivalent to 218 kg lint (Wanjura et al., 2014).

SWAT model calibration

The streamflow data were divided into two parts, and the data for the 1994–2001 and 2002–2009 periods were used for model calibration and validation, respectively. The SWAT model calibration was performed in three steps. First of all, the sensitive model parameters were identified by performing sensitivity analysis using the SWAT-CUP (Abbaspour et al., 2007; Veith et al., 2010; Arnold et al., 2012). In the second step, auto-calibration was performed using the SUFI-2 procedure available in the SWAT-CUP. During this step, sensitive model parameters were adjusted within ±10% range to obtain calibrated parameters for the study watershed. Finally, the calibrated parameters were slightly adjusted manually to achieve the best calibrated SWAT model for the watershed. The model was initially calibrated against the observed streamflow data recorded at Gauge I by adjusting the parameters in all sub-basins that contributed flow to Gauge I. The model was then validated against the remaining streamflow data recorded at Gauge I. After achieving a satisfactory calibration of the model for Gauge I, the model was calibrated against the streamflow data recorded at Gauge II. To start with, the calibrated parameter values that were obtained from model calibration for Gauge I were used in

Table 1 Simulated management practices for cotton and winter wheat in SWAT

No.	Operations	Description	Input data
	Irrigated cotton		
1	Tillage parameters (Tillage on April 1)		
	TILL_ID	Tillage ID	Generic spring plowing†
2	Fertilizer application parameters (May 1)		
	FERT_ID	Fertilizer ID	Urea
	FRT_KG	Amount of fertilizer applied to HRU	300.7 (kg ha^{-1})†
3	Begin growing season parameters (Planting on May 15)		Default
	Heat units to maturity		2354°C-day‡
4*	Auto-irrigation parameters (Start date: May 15; End date: October 31)		
	WSTRS_ID	Water stress identifier	Plant water demand
	IRR_SCA	Irrigation source	Shallow aquifer
	AUTO_WSTRS	Water stress threshold	0.9
	IRR_EFF	Irrigation efficiency	0.80†
5	Harvest and kill parameters (Kill on October 31)		Default
	Dryland cotton		
1	Tillage parameters (Tillage on April 1)		
	TILL_ID	Tillage ID	Generic spring plowing†
2	Fertilizer application parameters (May 1)		
	FERT_ID	Fertilizer ID	Urea
	FRT_KG	Amount of fertilizer applied to HRU	150 (kg ha^{-1})†
3	Begin growing season parameters (planting on May 15)		Default
	Heat units to maturity		2354°C-day‡
4	Harvest and kill parameters (Kill on October 31)		Default
	Winter wheat		
1	Tillage parameters (Tillage on October 8)		
	TILL_ID	Tillage ID	Generic fall plowing†
2	Fertilizer application parameters (October 8)		
	FERT_ID	Fertilizer ID	Urea
	FRT_KG	Amount of fertilizer applied to HRU	108 (kg ha^{-1})†
3	Begin growing season parameters (planting on October 15)		Default
	Heat units to maturity		1518°C-day‡
4	Harvest and Kill parameters (Kill on July 1)		Default

*Auto-irrigation was simulated in appropriate proportion of cotton area based on county cotton irrigation acreage summary reports.
†The management methods and parameters were based on published reports and local expertise.
‡Heat units to maturity for cotton and winter wheat were estimated using the SWAT-PHU program (http://swat.tamu.edu/software/potential-heat-unit-program/).

all sub-basins between Gauge I and Gauge II, and later, they were adjusted as needed to obtain a better match between the simulated and observed streamflow at Gauge II. The model was finally validated based on the remaining streamflow data recorded at Gauge II.

The highly sensitive curve number (CN2) was decreased by 6.5% for all of the sub-basins that discharged to Gauge I, and it was decreased by 9% for other sub-basins to reduce the surface runoff and thereby obtain a good match between the simulated and observed streamflow in the watershed (Table 2). The available soil water capacity (SOL_AWC) was increased by 10% for all sub-basins to further improve the match between the simulated and observed streamflow. The soil evaporation compensation factor (ESCO) was decreased from a default value of 0.95 to 0.855 in order to increase the soil evaporation and adjust crop yield prediction. A base flow recession constant (ALPHA_BF) of

0.0765, which was obtained from the base flow filter method (Arnold *et al.*, 1995; Arnold & Allen, 1999), was used.

After achieving a satisfactory streamflow calibration, the model was further calibrated for prediction of cotton lint yield under both irrigated and dryland systems to obtain a good match between the simulated and reported cotton lint yields. Previous SWAT modeling studies that performed crop yield calibration (Hu *et al.*, 2007; Nair *et al.*, 2011; Sarkar *et al.*, 2011; Ávila-Carrasco *et al.*, 2012) suggested adjusting the biomass/ energy ratio (BIO_E) and maximum leaf area index (BLAI) to calibrate the SWAT model for crop yield prediction. Among these studies, Sarkar *et al.* (2011) compared observed and simulated cotton lint yields, and they suggested the parameter ranges of BIO_E (10–20), BLAI (2–6) and light extinction coefficient (EXT_COEF; 0.5–0.8) for calibrating cotton lint yield. Following the procedure of Sarkar *et al.* (2011), the parameters

Table 2 Default and calibrated values of some important hydrologic and crop parameters in SWAT

No.	Parameter	Description	Default value	Calibrated value	Reference
Hydrologic parameters					
1	ESCO	Soil evaporation compensation factor	0.95	0.855	–
2	SOL_AWC	Available soil water capacity (mm H$_2$O mm^{-1} soil)	0.1–0.17	Increased by 10%	–
3	CN2	Curve number for moisture condition II	39–84	Decreased by 6.5% or 9%*	–
4	ALPHA_BF	Base flow recession constant	0.048	0.0765†	–
Dryland cotton parameters					
5	BIO_E	Biomass/energy ratio [(kg ha^{-1})/(MJ m^{-2})]	15	16.8	Sarkar *et al.* (2011)
6	HVSTI	Harvest index [(kg ha^{-1})/(kg ha^{-1})]	0.5	0.49	Wanjura *et al.* (2014)
7	BLAI	Max leaf area index (m^2/m^2)	4	4.5	Sarkar *et al.* (2011)
Irrigated cotton parameters					
8	BIO_E	Biomass/energy ratio [(kg ha^{-1})/(MJ m^{-2})]	15	19.95	Sarkar *et al.* (2011)
9	BLAI	Max leaf area index (m^2/m^2)	4	5.98	Sarkar *et al.* (2011)
10	EXT_COEF	Light extinction coefficient	0.65	0.78	Sarkar *et al.* (2011)

*Curve number decreased by 6.5% all of the sub-basins that discharged to Gauge I and decreased by 9% for other sub-basins.
†Obtained from baseflow filter method.

BIO_E, BLAI and EXT_COEF were adjusted within their reported ranges in this study. For the dryland cotton, BIO_E and BLAI of the crop database were increased from default values of 15 and 4 to 16.8 and 4.5, respectively (Table 2). The harvest index (HVSTI) was decreased from 0.5 to 0.49 based on the reported HVSTI value for the dryland cotton production systems in this region (Wanjura *et al.*, 2014). The BIO_E and BLAI were increased to 19.95 and 5.98, respectively, and EXT_COEF was changed from 0.65 to 0.78 for the irrigated cotton production systems (Table 2). Finally, after achieving a good crop yield calibration, the model performance in streamflow prediction was re-evaluated and necessary minor adjustments to initially calibrated streamflow related parameters were made.

Evaluating the performance of the SWAT model

The SWAT model performance in streamflow prediction during calibration and validation periods was evaluated using four different statistical measures: square of Pearson's product-moment correlation coefficient (R^2) (Legates & McCabe, 1999), Nash–Sutcliffe efficiency (*NSE*) (Nash & Sutcliffe, 1970), index of agreement (*d*) (Willmott, 1981) and percent bias (*PBIAS*). The model performance in cotton lint yield prediction was assessed using the *PBIAS* only.

The R^2 represents the proportion of total variance in the observed data that can be explained by the model. The R^2 ranges from 0 to 1 with higher values denoting better model performance. The *NSE* indicates how well the plot of observed vs. simulated values fits on the 1 : 1 line. It ranges from $-\infty$ to 1, and the *NSE* values closer to 1 indicate the better model performance. The *d* varies from 0 (no correlation) to 1 (perfect fit), and it overcomes the insensitivity of R^2 and *NSE* to differences in the observed and simulated means and variances (Willmott, 1981). The *PBIAS* varies between -100 and ∞, with smaller absolute values closer to 0 indicating better agreement. In this study, we aimed to achieve *NSE*, R^2, *d* and *PBIAS* of > 0.6,

> 0.65, > 0.9 and within ±15%, respectively, during the model calibration and validation periods.

Water use efficiency

The water use efficiency (WUE; kg ha^{-1} mm^{-1}) of both dryland and irrigated bioenergy crops was estimated and compared over the model simulation period. The WUE of the dryland systems was estimated as (Musick *et al.*, 1994; Howell, 2001):

$$WUE = \frac{B_d}{ET} \qquad (2a)$$

where B_d is the biomass yield (kg ha^{-1} year^{-1}) under dryland systems, and ET is the evapotranspiration (mm year^{-1}).

The WUE of irrigated systems (IWUE; kg ha^{-1} mm^{-1}) was estimated using the following relationship:

$$IWUE = \frac{B_i - B_d}{I} \qquad (2b)$$

where B_i is the biomass yield (kg ha^{-1} year^{-1}) under irrigated systems, and I is the amount of irrigation water application in millimeter per year (Bos, 1980).

Scenario analysis

For the scenario analysis, four promising cellulosic bioenergy crops, switchgrass, *Miscanthus*, big bluestem and biomass sorghum were selected to hypothetically replace cotton. The impacts of these land use changes on water balances over the period from 1994 to 2009 were evaluated. The impacts were assessed both at the watershed scale and only among the HRUs where cotton was grown under baseline condition (hereafter referred as 'baseline cotton HRUs'). In addition, the land use change impacts under both irrigated and dryland systems were compared and contrasted.

In the scenario analysis, perennial grasses were planted on May 15, 1992, and harvested on November 15th of each year to

maximize biomass potential (Griffith *et al.*, 2014; Hudiburg *et al.*, 2015). The annual biomass sorghum was planted on June 1st and harvested on October 31st of each year (Hao *et al.*, 2014) (Table S1). In the baseline cotton HRUs where irrigated cotton was simulated, cellulosic bioenergy crops were also assigned the same irrigation management practices as cotton. For switchgrass and big bluestem, about 270 and 180 kg ha^{-1} of urea was applied on irrigated and dryland systems, respectively (Yimam *et al.*, 2014). About 320 and 214 kg ha^{-1} of urea was applied under irrigated and dryland *Miscanthus* scenarios, respectively (Lewandowski & Schmidt, 2006; Danalatos *et al.*, 2007). Approximately 360 and 240 kg ha^{-1} of urea were applied on irrigated and dryland biomass sorghum, respectively (Hao *et al.*, 2014; Yimam *et al.*, 2014) (Table S1). In all hypothetical land use change scenarios, tillage was not simulated. Heat units to maturity for cotton, winter wheat and the cellulosic bioenergy crops were estimated using the SWAT Potential Heat Unit (SWAT-PHU) program (http://swat.tamu.edu/software/potential-heat-unit-program/). The values of heat units to maturity of these crops are shown in Table 1 and Table S2.

Miscanthus is an emerging commercial bioenergy crop, and crop growth parameters for this crop are lacking in the SWAT crop database (Ng *et al.*, 2010). We therefore adopted the *Miscanthus* growth parameters from Trybula *et al.* (2014) field study at the Purdue University Water Quality Field Station in northwestern Indiana. The harvest efficiency of *Miscanthus* was taken as 0.7 based on Trybula *et al.* (2014) study. The harvest efficiency of 0.75 reported by Trybula *et al.* (2014) for Shawnee switchgrass was used for Alamo switchgrass and big bluestem in this study. Based on the similarities in physiological characteristics of *Miscanthus* and switchgrass, *Miscanthus* was assigned the same Soil Conservation Service (SCS) runoff curve numbers as that of switchgrass (Love & Nejadhashemi, 2011; Trybula *et al.*, 2014). The default curve number values for the selected bioenergy crops were modified by the same percentage as those for cotton crop (baseline) during the model calibration. The detailed crop growth parameters for the selected cellulosic bioenergy crops are included in Table S2.

Results

SWAT calibration and validation

The simulated monthly streamflow at two USGS gauges during the calibration (1994–2001) and validation (2002–2009) periods closely matched with the observed streamflow (Figs. S1 and S2). The *NSE*, R^2, *d* and *PBIAS* values for monthly predictions of streamflow at Gauge I were 0.78, 0.87, 0.95 and −6.3%, respectively, and those at Gauge II were 0.66, 0.66, 0.88 and −4.1%, respectively, during the model calibration period, demonstrating a 'very good' to 'good' agreement between the simulated and observed streamflow according to Moriasi *et al.* (2007) criteria (Table 3). The model performance in predicting streamflow during the validation period was also in the range of 'good' (based on the *NSE* and *PBIAS* of 0.66 and 10.8% for Gauge II) to 'satisfactory' (based on the *NSE* and *PBIAS* of 0.59 and −6.4% for Gauge I) according to Moriasi *et al.* (2007) criteria.

Lower *NSE* value for the Gauge I during the validation period was mainly due to an overprediction of streamflow in November 2004 and an underprediction in October 2006 (Fig. S1b). Accurate prediction of streamflow by the SWAT model during wet (high rainfall) periods such as those in November 2004 in this study was particularly challenging due to the use of the SCS runoff curve number method, and this limitation of the model (Garen & Moore, 2005; White *et al.*, 2009; Rathjens *et al.*, 2015) might have caused the poor predictions in that month at Gauge I. The under prediction of streamflow in October 2006 at Gauge I was most probably due to differences in precipitation data input to the model and the actual precipitation that occurred within the catchment of Gauge I (Fig. S1b). Although the precipitation recorded at three rain gauges within the area of influence of the Gauge I on October 15 and 16, 2006, was < 30 mm, the observed streamflow on the above dates was 76 and 50 mm, respectively, indicating potential errors in precipitation input.

Cotton lint yield comparison

After calibrating for streamflow prediction, the SWAT model was calibrated for cotton lint yield prediction in the Lynn County. Results showed that the average *PBIAS* in predicting dryland cotton lint yield over the calibration and validation periods was −2.6% and

Table 3 Monthly statistical parameters for the model streamflow calibration and validation on two USGS gauges

Time scale	Gauge I		Gauge II	
	Calibration (1994–2001)	Validation (2002–2009)	Calibration (1994–2001)	Validation (2002–2009)
Nash–Sutcliffe efficiency	0.78 (Very good*)	0.59 (Satisfactory)	0.66 (Good)	0.66 (Good)
R^2	0.87	0.69	0.66	0.72
Index of agreement	0.95	0.90	0.88	0.92
Percent bias (%)	−6.3 (Very good)	−6.4 (Very good)	−4.1 (Very good)	10.8 (Good)

*General model performance ratings suggested by Moriasi *et al.* (2007) for monthly predictions of streamflow.

2.4%, respectively, and the *PBIAS* over the entire time period (1994–2009) was 0.4%, indicating a good match between the simulated and observed cotton lint yields (Table 4). In case of irrigated cotton, the average *PBIAS* in yield prediction was 12.7% and −14.5% during the calibration and validation periods, respectively, representing a satisfactory agreement between the simulated and observed cotton lint yields. However, the model hugely overpredicted cotton lint yield under irrigated systems in 1998, which was an extremely dry year

Table 4 Comparison of cotton lint yield for Lynn County (Mg ha^{-1})

Years	Simulated lint yield	Observed lint yield	*PBIAS* (%)
Dryland cotton			
1994	0.27	0.25	8
1995	0.09	0.18	−51
1996	0.32	0.39	−20
1997	0.22	0.32	−33
1998	0.37	0.37	1
1999	0.45	0.38	20
2000	0.36	0.23	58
2001	0.19	0.20	−8
Average for calibration period	0.28	0.29	−2.6
2002	0.28	0.27	5
2003	0.27	0.26	2
2004	0.47	0.58	−18
2005	0.71	0.70	1
2006	0.57	0.33	75
2007	0.61	0.65	−6
2008	0.24	0.31	−22
2009	0.43	0.40	6
Average for validation period	0.45	0.44	2.4
Overall (1994–2009)	0.37	0.36	0.4
Irrigated cotton			
1994	0.72	0.71	2
1995	0.32	0.53	−39
1996	0.56	0.62	−9
1997	0.33	0.55	−41
1998	1.37	0.64	115
1999	0.66	0.55	18
2000	0.69	0.50	40
2001	0.63	0.60	6
Average for calibration period	0.66	0.59	12.7
2002	0.77	0.74	3
2003	0.67	0.67	1
2004	0.80	0.88	−8
2005	1.11	1.05	6
2006	1.30	0.92	42
2007	0.34	0.96	−64
2008	0.52	0.88	−41
2009	0.48	0.92	−47
Average for validation period	0.75	0.88	−14.5
Overall (1994–2009)	0.71	0.73	−3.6

(annual rainfall about 300 mm). The auto-irrigation option used in this study, which did not consider actual availability of irrigation water in a dry year, led to this overprediction of cotton lint yield under irrigated systems.

Simulated water balances under baseline and hypothetical land use change scenarios

At the watershed scale, on an average (1994–2009), results showed that about 94% of the input water (precipitation + irrigation) was lost due to ET (Table 5a). The changes in ET with reference to the baseline cotton scenario were within ±3% under all hypothetical land-use change scenarios. Under perennial grass scenarios, the average annual surface runoff and water yield decreased by about 6–8% and 3–4%, respectively, when compared to the baseline cotton scenario (Table 5a). However, when cotton was replaced by biomass sorghum, the average annual surface runoff and water yield increased by about 5% and 3%, respectively. Under the hypothetical perennial grass land use change scenarios, average annual percolation increased within a range of 3–22%, as compared to the baseline cotton scenario.

The monthly water balance analysis showed that the peak ET occurred in June or July under all land use change scenarios (Fig. 3). The monthly surface runoff apparently decreased under perennial grass scenarios during high rainfall months (June, August and September) when compared to the baseline cotton and biomass sorghum scenarios (Fig. 4). The reduction in surface runoff under perennial grass scenarios and the decrease in ET during August to October under cellulosic bioenergy crop scenarios as compared to the baseline cotton scenario resulted in a higher soil water content under cellulosic bioenergy crop scenarios from August to April (Fig. 5).

Among the baseline cotton HRUs, the percent changes in all water balance parameters, except ET, under hypothetical land use change scenarios increased substantially (Table 5b). For example, average (1994–2009) annual surface runoff under perennial grass scenarios decreased within a range of 77–93% compared to the baseline cotton scenario. In the irrigated baseline cotton HRUs, auto-irrigation was used to optimally meet the crop water needs, which highlighted the differences in water requirements of the studied crops. Results showed that *Miscanthus* required the highest amount of irrigation water among all crops (Table 5c). However, the percent changes in water balances for the irrigated baseline cotton HRUs could be somewhat misleading as the amount of irrigation water applied for the simulated crops was not the

Table 5 Comparison of the average (1994–2009) annual water balance parameters under baseline and hypothetical land use change scenarios in the entire watershed and baseline cotton HRUs

Unit (mm)	Cotton	Switchgrass	*Miscanthus*	Big bluestem	Biomass sorghum
(a) Entire watershed					
Precipitation	520.1	520.1	520.1	520.1	520.1
Irrigation	25.7	26.5 (3.0*)	34.0 (17.5)	16.7 (−35.3)	11.9 (−53.8)
Evapotranspiration	515.7	516.4 (0.1)	518.3 (0.5)	507.1 (−1.7)	501.0 (−2.9)
Surface runoff	11.2	10.4 (−7.3)	10.5 (−6.3)	10.4 (−7.8)	11.8 (4.9)
Percolation	10.5	11.4 (8.7)	12.8 (22.2)	10.8 (2.8)	10.6 (0.9)
Water yield	21.1	20.3 (−3.6)	20.5 (−2.6)	20.2 (−4.0)	21.6 (2.6)
(b) Baseline cotton HRUs (irrigated and dryland combined)					
Precipitation	497.2	497.2	497.2	497.2	497.2
Irrigation	82.9	85.4 (3.0)	97.4 (17.5)	53.6 (−35.3)	38.2 (−53.8)
Evapotranspiration	575.3	577.5 (0.4)	583.7 (1.5)	547.7 (−4.8)	528.0 (−8.2)
Surface runoff	3.0	0.4 (−88)	0.7 (−77)	0.20 (−93)	4.8 (59)
Percolation	0.003	2.9	7.5	1.0	0.30
Water yield	3.7	1.3 (−65)	1.9 (−47)	0.9 (−75)	5.4 (48)
(c) Baseline irrigated cotton HRUs					
Precipitation	483.7	483.7	483.7	483.7	483.7
Irrigation	276.0	284.3 (3.0)	324.3 (17.5)	178.5 (−35.3)	127.1 (−53.8)
Evapotranspiration	754.0	759.9 (0.8)	790.6 (4.9)	658.2 (−12.7)	602.2 (−20.1)
Surface runoff	3.4	0.55 (−84)	0.9 (−74)	0.2 (−94)	5.8 (70)
Percolation	0.001	6.7	14.6	2.1	0.59
Water yield	4.6	2.2 (−52)	3.1 (−32)	1.4 (−70)	6.8 (47)
(d) Baseline dryland cotton HRUs					
Precipitation	502.9	502.9	502.9	502.9	502.9
Evapotranspiration	498.5	499.1 (0.1)	494.9 (−0.7)	500.2 (0.3)	496.1 (−0.5)
Surface runoff	2.81	0.27 (−90)	0.62 (−78)	0.20 (−93)	4.3 (54)
Percolation	0.004	1.3	4.5	0.5	0.17
Water yield	3.3	0.9 (−74)	1.4 (−57)	0.7 (−78)	4.8 (48)

*The number in the parentheses is the percent change with each cellulosic bioenergy crop scenario relative to baseline cotton scenario.

same as that applied to cotton under the baseline scenario due to implementation of auto-irrigation (Table 5b,c).

The water balance assessments within the dryland baseline cotton HRUs (Table 5d) represented appropriate comparison of scenarios as precipitation, which was the same for all scenarios, was the only source of input water. The average (1994–2009) annual ET within the dryland baseline cotton HRUs was nearly the same under all scenarios (Table 5d). The average annual surface runoff was almost negligible under perennial grass scenarios, but it increased from 2.8 mm under the baseline cotton scenario to 4.3 mm under the biomass sorghum scenario (a 54% increase). When compared to the baseline cotton scenario, there is a considerable increase in average annual percolation and average monthly soil water content during August to April under different cellulosic bioenergy crop scenarios (Table 5d; Fig. 5c). This is a very important finding from this study in view of depleting groundwater levels in the Ogallala aquifer. It is expected that most of the currently irrigated lands

in the SHP could eventually be converted into drylands in the future, and replacing cotton with bioenergy crops under those circumstances could therefore not only improve soil water content, but also contribute to groundwater recharge.

The simulated emergence of perennial grasses in the study watershed began around April. This is in consistence with Yimam *et al.* (2015), who reported that the emergence of switchgrass occurred between mid-March and mid-April in a field experiment at Stillwater in Oklahoma. VanLoocke *et al.* (2010) also reported that perennial crops emergence in mid- to late April in the Midwestern United States, about a month earlier than most annual crops. Monthly water balance analysis in the dryland baseline cotton HRUs indicated that the peak ET occurred one month early under the perennial grass scenarios when compared to the baseline cotton and biomass sorghum scenarios (Fig. 3c). The ET in irrigated baseline cotton HRUs during June to August was almost twice of that in the dryland baseline cotton HRUs (Fig. 3b and c). There was a
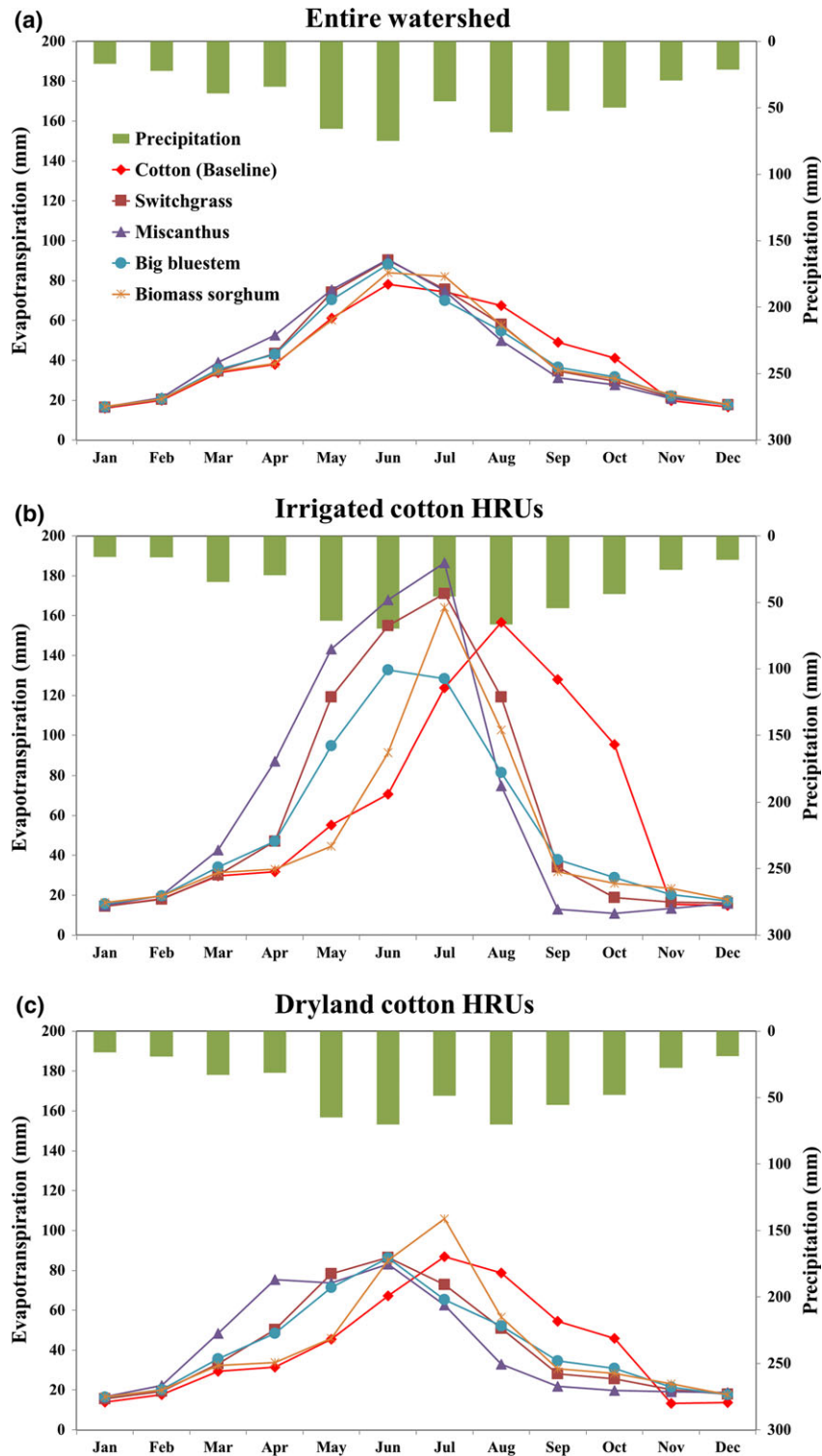
Fig. 3 Average (1994–2009) monthly variability of evapotranspiration under entire watershed and irrigated and dryland baseline cotton hydrologic response units (HRUs).

negligible generation of surface runoff under perennial grass scenarios (Fig. 4b and c). The lowest soil water content under perennial grass scenarios was simulated

one month earlier when compared to the baseline cotton scenario (Fig. 5b and c). This was associated with the early occurrence of peak ET under perennial grass
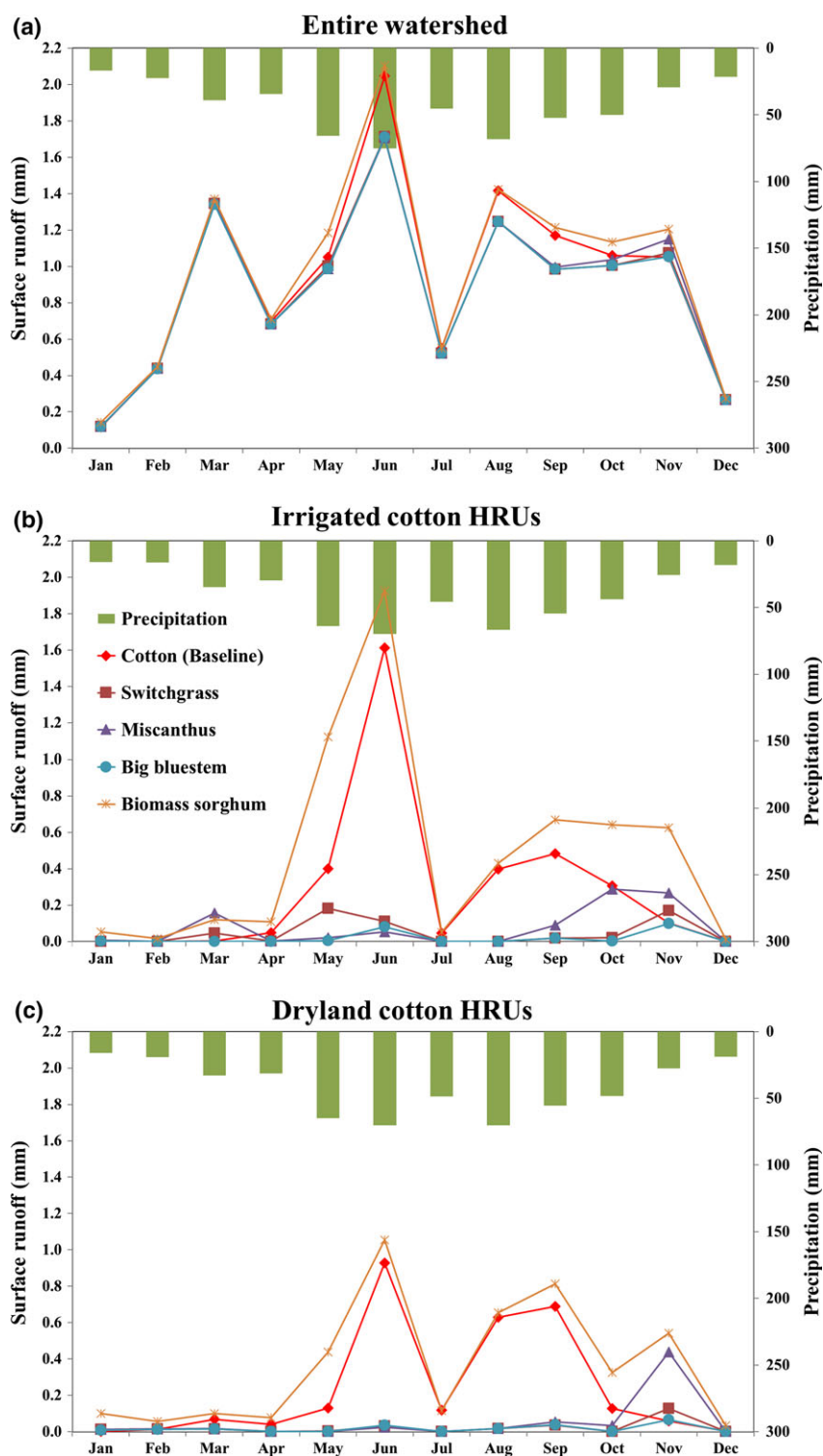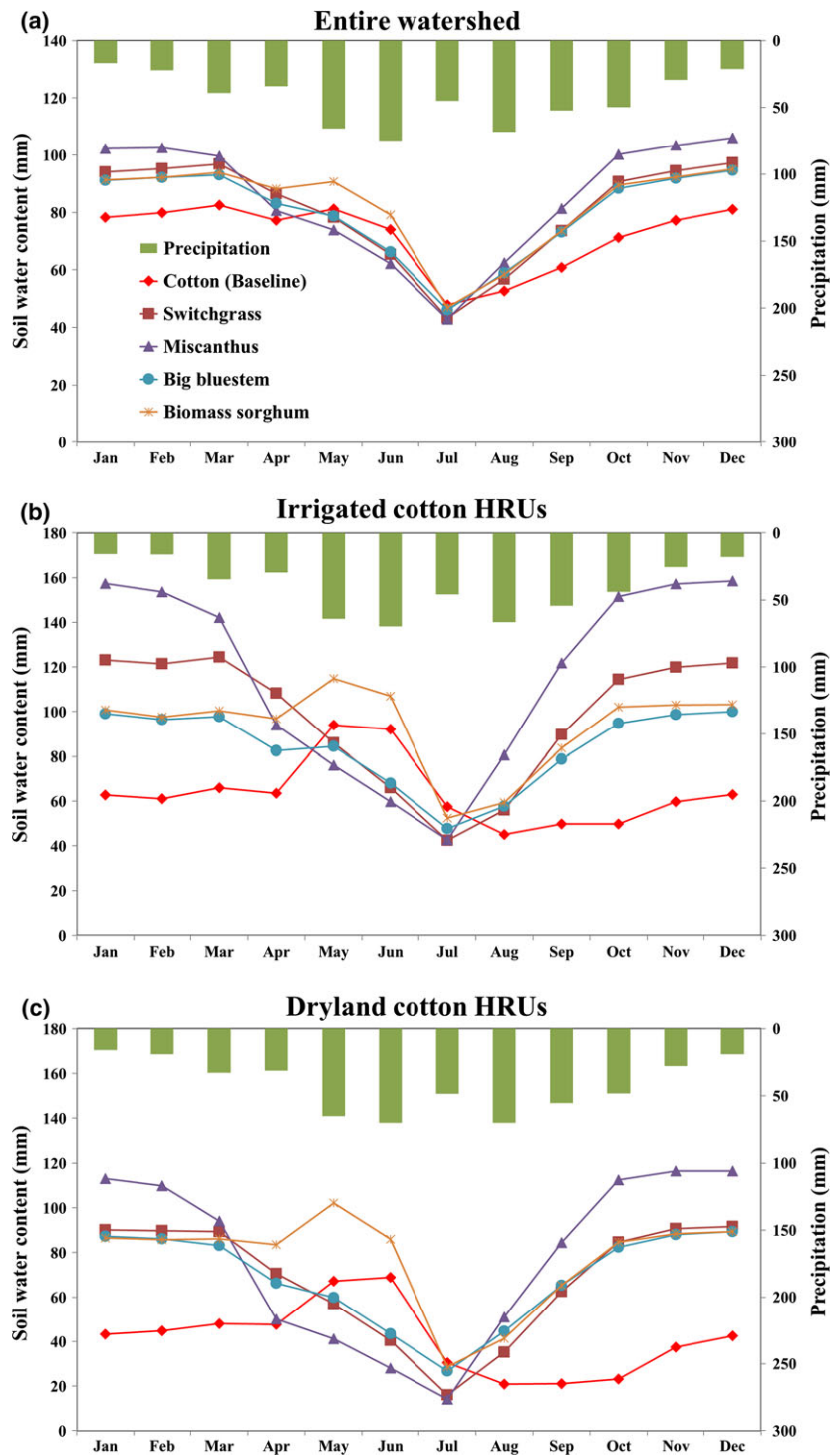
Fig. 4 Average (1994–2009) monthly variability of surface runoff under entire watershed and irrigated and dryland baseline cotton hydrologic response units (HRUs).

scenarios by one month relative to the baseline cotton scenario. Clearly, higher soil water storage was simulated in the irrigated baseline cotton HRUs during the whole year when compared to the dryland baseline cotton HRUs due to the application of irrigation water (Fig. 5).

Fig. 5 Average (1994–2009) monthly variability of soil water content under entire watershed and irrigated and dryland baseline cotton hydrologic response units (HRUs).

Biomass and biofuel production potential and water use efficiency

The simulated average (1994–2009) annual harvestable biomass under *Miscanthus*, switchgrass, big bluestem

and biomass sorghum scenarios was 19.1, 11.1, 3.2 and 8.8 Mg ha^{-1}, respectively, when both irrigated and dryland baseline cotton HRUs were combined (Table 6). It is worth noting that the simulated biomass production under the irrigated systems was higher by about

Table 6 Average (1994–2009) annual biomass and biofuel production, and water use efficiency of switchgrass, *Miscanthus*, big bluestem and biomass sorghum under hypothetical land use change scenarios

Average value	Switchgrass	*Miscanthus*	Big bluestem	Biomass sorghum
Baseline cotton HRUs (irrigated and dryland combined)				
Biomass production (Mg ha^{-1})	11.1	19.1	3.2	8.8
Biofuel production* (liter ethanol ha^{-1})	3123	5374	896	2482
Baseline irrigated cotton HRUs				
Biomass production (Mg ha^{-1})	17.5	27.1	4.2	11.6
Biofuel production (liter ethanol ha^{-1})	4931	7548	1170	3271
Irrigated water use efficiency (kg ha^{-1} mm^{-1})	32.2	35.5	7.8	31.5
Baseline dryland cotton HRUs				
Biomass production (Mg ha^{-1})	8.3	15.6	2.8	7.6
Biofuel production (liter ethanol ha^{-1})	2347	4398	778	2143
water use efficiency (kg ha^{-1} mm^{-1})	16.7	31.5	5.5	15.3

*Based on current biofuel conversion efficiency of 282 L ethanol Mg^{-1} biomass (Lynd *et al.*, 2008; Fargione *et al.*, 2010).

50–111% when compared to the dryland systems (Table 6). Based on current biofuel conversion efficiency of 282 L ethanol Mg^{-1} biomass (Lynd *et al.*, 2008; Fargione *et al.*, 2010), *Miscanthus* and switchgrass exhibited superior ethanol production potential compared to biomass sorghum and big bluestem under both irrigated and dryland systems (Table 6). The estimated average annual quantity of ethanol that could be produced with the simulated biomass of *Miscanthus*, switchgrass, big bluestem and biomass sorghum was 7548, 4931, 1170 and 3271 L ha^{-1}, respectively, under the irrigated systems, and 4398, 2347, 778 and 2143 L ha^{-1}, respectively, under the dryland systems (Table 6). The simulated WUEs under the dryland *Miscanthus*, switchgrass, big bluestem and biomass sorghum scenarios were 32, 17, 6 and 15 kg ha^{-1} mm^{-1}, respectively (Table 6). The simulated IWUEs ranged from 8 to 36 kg ha^{-1} mm^{-1} with the highest IWUE simulated under *Miscanthus* scenario (36 kg ha^{-1} mm^{-1}), followed by switchgrass scenario (32 kg ha^{-1} mm^{-1}).

Discussion

Evaluation of SWAT model performance

For the hydrologic model evaluations performed on a monthly time step, Moriasi *et al.* (2007) proposed that *NSE* values should exceed 0.5, 0.65 and 0.75, and *PBIAS* should be within ±25%, ±15% and ±10% in order for model performance to be judged as 'satisfactory', 'good' and 'very good', respectively. According to this criteria, the model performance in this study was between 'very good' and 'good' during the calibration period and was between 'satisfactory' and 'good' during the validation period (Table 3). Harmel *et al.* (2014) recommended considering the model's intended use while evaluating the model performance. As this study mainly focused on

assessing the influence of land use change on watershed hydrology on a monthly or annual basis, achieving good model performance on a monthly time step was considered as acceptable to use the calibrated SWAT model for scenario analysis. Comparison of the predicted cotton lint yields with the NASS-reported county-wise yields within the study watershed under both dryland and irrigated systems indicated that they both matched well (Table 4), and this additional evaluation further enhanced confidence in the calibrated model.

In this study, high interannual variability in *PBIAS* in cotton lint yield prediction existed in some years (Table 4). The long-term observed cotton lint yields used in this study were available at the county level (NASS). However, the SWAT model simulated cotton lint yields at the sub-basin/HRU level, and hence, simulated yields might not have spatially represented the observed county-wise yields very well. Also, the SWAT model was setup with 2008 NASS-CDL land use in this study, and it was assumed that the cotton planting area was the same during the whole simulation period. The crop growth algorithm of the SWAT model is also not capable of taking into account the genetic improvements of crops in the long-term predictions. In addition, the use of auto-irrigation option provided more timely and adequate water for cotton growth, but in reality, water-limiting conditions might have existed for cotton production in the study watershed. For example, the year 1998 was a very dry year with an annual precipitation of 300 mm, and hence, observed cotton lint yield was about 0.64 Mg ha^{-1}. However, because of auto-irrigation and non-water-limiting conditions, more irrigation water was applied in that year, which has resulted in a very high simulated yield of 1.37 Mg ha^{-1}, and a huge *PBIAS* of 115%. Several of the aforementioned reasons might have led to high interannual variability in *PBIAS* in this study.

Hydrological responses of hypothetical land use change scenarios

An important factor for environmental evaluation of land use change is the assessment of associated hydrological responses. In this study, changes in hydrological fluxes of ET, surface runoff, soil water content, percolation and water yield under various hypothetical land-use change scenarios were studied. The dominant component of the water balance in the study watershed is the water lost through ET, which accounted for about 94% of the input water (precipitation + irrigation). This is comparable with the ET losses from biomass sorghum production systems in the Texas High Plains reported in Hao *et al.* (2014), which stated that more than 90% of the growing season precipitation was lost as growing season ET. The crop available water in this semi-arid study watershed is very limited because of low annual precipitation (520 mm). In general, crop ET under the irrigated systems was higher than that under the dryland systems because of the much higher annual potential ET of 1700 mm (as estimated by the SWAT model) than the highest total input water in this region (e.g. 808 mm under irrigated *Miscanthus* scenario). For example, the ET of *Miscanthus* under the irrigated systems was higher by about 60% when compared to *Miscanthus* under the dryland systems (Table 5c,d). *Miscanthus* requires more irrigation water than cotton [16-year average irrigation amount of 324 mm (*Miscanthus*) vs. 276 mm (cotton)]. Higher water requirement and larger biomass production potential of *Miscanthus* (Heaton *et al.*, 2004) explained the apparent increase in ET under the irrigated *Miscanthus* scenario when compared to the irrigated baseline cotton scenario (Table 5c). However, the irrigation water requirement of switchgrass, big bluestem and biomass sorghum were similar to or less than that of cotton (baseline scenario) (Table 5c). Therefore, there is a potential for maintaining or reducing groundwater withdrawals from the Ogallala Aquifer when irrigated cotton is replaced by switchgrass, big bluestem and biomass sorghum.

Assessment of water balances among the dryland baseline cotton HRUs represents a more appropriate comparison of scenarios as it eliminates differential amounts of irrigation water simulated for the studied crops due to the implementation of auto-irrigation. Within the dryland baseline cotton HRUs, crop ET values of all simulated bioenergy crops were almost the same as that of cotton, and it accounted for about 98% of annual rainfall (Table 5; Fig. 3c). The surface runoff and water yield were apparently reduced within a range of 78–93% and 57–78%, respectively, under perennial grass scenarios compared to the baseline cotton scenario (Table 5d). More importantly, the peak surface runoff in high rainfall months of May, June, August and September decreased by a huge proportion under the perennial grass scenarios (Fig. 4). In contrast, the surface runoff and water yield increased by about 54% and 48%, respectively, under the biomass sorghum scenario when compared to the baseline cotton scenario (Table 5d). The higher biomass density and lower surface runoff potential (average calibrated curve number of 54.4) of the perennial grasses as compared to cotton (average calibrated curve number of 71.0) contributed to the reduction in surface runoff and water yield. Le *et al.* (2011) also found that land use change from maize to *Miscanthus* and switchgrass decreased the surface runoff by 24 and 6 mm, respectively, in the Midwestern United States. In the case of biomass sorghum scenario, shorter growing period and lesser ground cover after harvest compared to cotton contributed to higher surface runoff (16-year average surface runoff of 4.3 mm (biomass sorghum) vs. 2.8 mm (cotton), a 54% increase) and water yield (16-year average water yield of 4.8 mm (biomass sorghum) vs. 3.3 mm (cotton), a 48% increase).

Results have also showed that the average annual percolation increased considerably under the perennial grass land use change scenarios relative to the baseline cotton scenario (Table 5d). The monthly soil water content was higher under perennial grass scenarios compared to the baseline cotton scenario during August to April (Fig. 5c). Reduction in surface runoff was the dominant factor responsible for the increase in soil water content and percolation under perennial grass scenarios. However, the simulated monthly soil water content under the dryland *Miscanthus* scenario was lesser than that under the dryland baseline cotton scenario during the period from May to July (Fig. 5c). Some published studies from the Midwestern United States have also reported reductions in soil water content under *Miscanthus* due to the higher simulated ET when compared to corn (VanLoocke *et al.*, 2010; Le *et al.*, 2011).

Biomass production potential of selected cellulosic bioenergy crops

The simulated average (1994–2009) annual biomass yield was the highest (27.1 Mg ha^{-1}) under the irrigated *Miscanthus* scenario, followed by the irrigated switchgrass scenario (17.5 Mg ha^{-1}) (Fig. 6; Table 6). The simulated *Miscanthus* biomass yields from this study (27.1 and 15.6 Mg ha^{-1} under the irrigated and dryland systems, respectively; Table 6) were within the range of reported yields in the literature (5–44 Mg ha^{-1}) (Lewandowski *et al.*, 2000; Powelson *et al.*, 2005; Kindred *et al.*, 2008). More specifically, the predicted average annual *Miscanthus* biomass yield under the dryland systems in this study was also within the range of reported
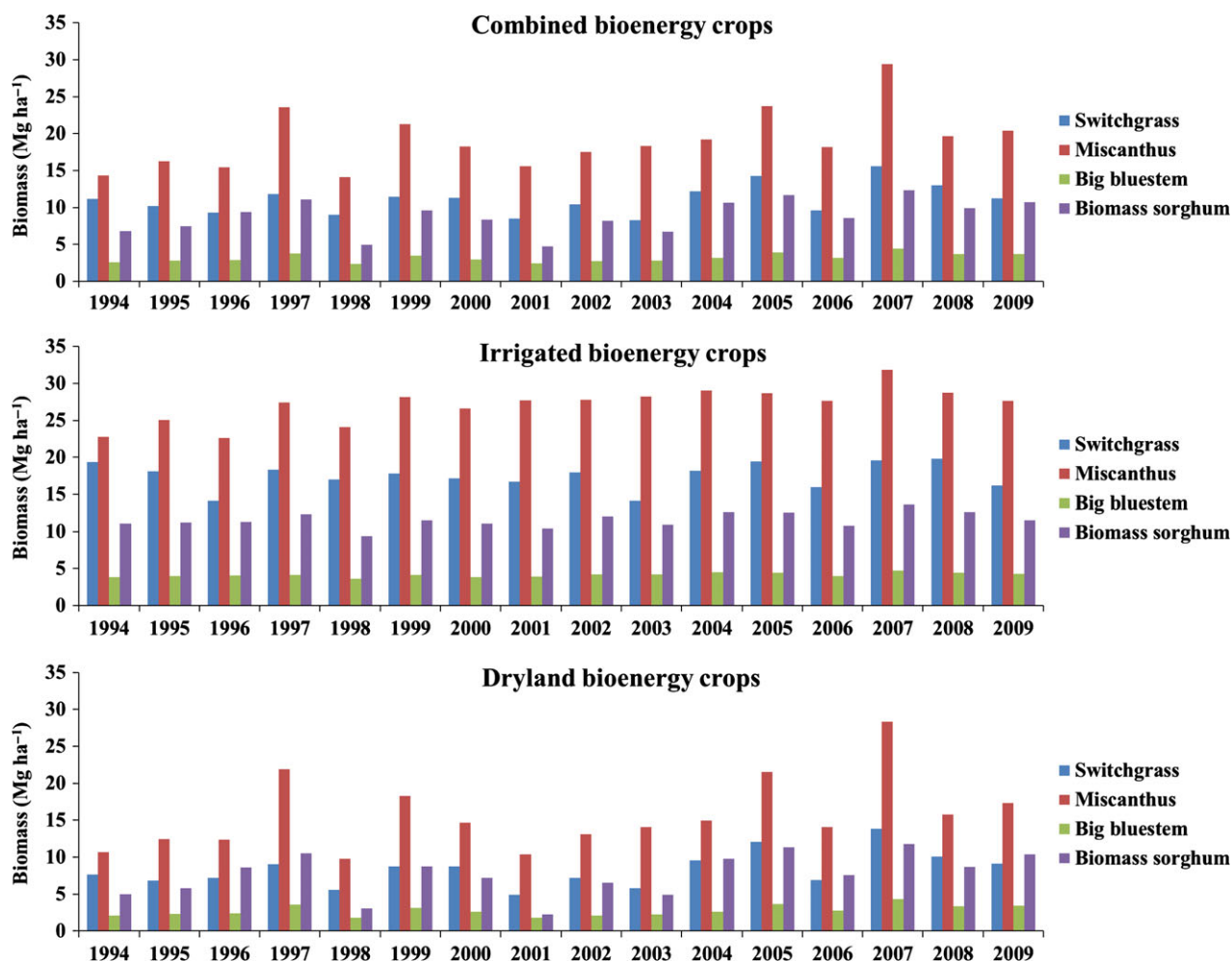
Fig. 6 Simulated average (1994–2009) annual biomass production from switchgrass, *Miscanthus*, big bluestem and biomass sorghum in combined, irrigated and dryland baseline cotton hydrologic response units (HRUs).

Miscanthus biomass yield (9.8–17.8 Mg ha^{-1}) in the dryland production systems in United Kingdom (U.K.) (Christian *et al.*, 2008). In addition, the simulated *Miscanthus* biomass yield under the irrigated systems was consistent with the irrigated *Miscanthus* biomass yield reported from the field experiments conducted in Portugal (26.9 Mg ha^{-1}; Clifton-Brown *et al.*, 2001) and Italy (27.1 Mg ha^{-1}; Cosentino *et al.*, 2007).

The predicted switchgrass biomass yields in this study were 17.5 and 8.3 Mg ha^{-1} under the irrigated and dryland systems, respectively. The simulated dryland switchgrass biomass yield in this study was within the range of measured biomass yields of 8.1–16.5 Mg ha^{-1} reported by McLaughlin & Adams (2005) for Dallas, College Station and Stephenville in Texas during the period from 1995 to 2000. The differences in dryland switchgrass biomass yield between this study and that of McLaughlin & Adams (2005) were most probably be due to the differences in average annual

precipitation. The study watershed receives much less annual precipitation compared to Dallas, College Station and Stephenville. Ocumpaugh *et al.* (1998) reported that a single mid-season irrigation event may double switchgrass yields in dry years in Texas. The results from the McLaughlin & Adams (2005) study also suggested that switchgrass yields could increase substantially in arid areas by low-frequency irrigation.

Among the simulated bioenergy crops, biomass sorghum generated more surface runoff than others (Table 5). In addition, biomass sorghum requires more management efforts for replanting it every year and for meeting additional transportation and harvesting requirements (Turhollow *et al.*, 2010). On the other hand, biomass production potential of big bluestem was much lower compared to that of *Miscanthus* and switchgrass (Fig. 6; Table 6). It was interesting to note that the simulated biomass yield under dryland *Miscanthus* was nearly the same as that of irrigated switchgrass. In

addition, *Miscanthus* showed the highest WUE among all rainfed land use change scenarios. This indicated that *Miscanthus* is a good bioenergy crop choice for large areas of dryland crop production systems in the study region. On the other hand, switchgrass recorded the second highest IWUE under the irrigated land use change scenarios. Furthermore, irrigated switchgrass demonstrated greater potential for effective water conservation when compared to the irrigated *Miscanthus*. Due to higher WUE/IWUE, better potential for water conservation, greater biomass and biofuel production potential, and minimum crop management, *Miscanthus* and switchgrass were therefore found to be ideal bioenergy crops for the dryland and irrigated systems in the study watershed, respectively.

Acknowledgements

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table S1. Simulated management practices for cellulosic bioenergy crops in SWAT.

Table S2. Crop growth parameters for all the selected cellulosic bioenergy crops.

Figure S1. Comparison of observed and simulated monthly streamflow at Gauge I during the model (a) calibration and (b) validation periods.

Figure S2. Comparison of observed and simulated monthly streamflow at Gauge II during the model (a) calibration and (b) validation periods.